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# NASA/JPL ePrognostics Technology to Support Fleet Remote Operations and Asset Health Management


## ABSTRACT

The first paper summarizes Naval Surface Warfare Center Port Hueneme Division's (NSWC PHD) efforts to investigate the NASA/Jet Propulsion Laboratory (JPL) ePrognostics tool to support remote operations, asset status, and health management. The analysis involves the adaption of NASA/JPL algorithms to the Navy SPY-1 Radar system, and the application of Six Sigma tools for both product evaluation and enhanced prediction protocols. The SPY-1 radar is the primary air and surface radar for the AEGIS Combat System.


## SPONSOR CLEARANCE

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## INTRODUCTION

This motivation behind this research is the fact that there is currently no capability to accurately predict system outages due to component failures. This capability would increase operational availability by forecasting, and by way of preventative maintenance avoiding, system and component failures. This technology would provide the operator the ability to accurately predict a system or component failure prior to the actual failure occurring. The more we know about when a failure is going to occur, the better prepared we can be to handle the upcoming problem. Subsequently, with the indication of an imminent failure, a reduction in logistic and administrative delay times are expected, as well as affording us the opportunity to locate other resources to satisfy mission requirements. We began our research by gathering data that had been previously collected from the AEGIS SPY-1 radar system's Transmitter Power and Phase Test (TPP). The TPP data was collected once per day over a 30-day period for all amplifier, array, band, and channel combinations. The objective of this research is to provide a significant and rigorous modeling and simulation effort to predict radar output power. In

collaboration with NASA/JPL, we developed time series forecasting models. Using the predictions from these models, we performed control chart analyses to determine out of control conditions. We used Excel, Minitab, and Matlab during this modeling and simulation effort.

## ANALYSIS

A simple but effective visual analysis was done by plotting the data for Band 1 Channels 5-8 (Figure 1) and inspecting it for quality and for any anomalies that may be visible. An immediate observation is that the data is fairly constant for the first 21 days and then starts to decrease on day 22. Knowing that the failure occurred on day 28, we now know that the decrease on day 22 was a warning sign that something was wrong. Our partners at NASA/JPL fit an autoregressive model equation with three autoregressive coefficients (Equation 1) to forecast the data. This model assumes that the value of each observation is a function, specifically: a linear combination, of the values of the previous three observations. Equation 1 defines the autoregressive forecasting model where for any day "n", the observed value for that day on channel a and band b is written: $x_n^{(a,b)}$. Hence, as measured in observation cycles from day n, the observation three days in the future $x_{n+3}^{(a,b)}$ is considered to be equal to a linear combination of observations: two days forward, $x_{n+2}^{(a,b)}$; one day forward, $x_{n+1}^{(a,b)}$; and on day n, $x_n^{(a,b)}$; with coefficients $\beta_1^{(a,b)}$, $\beta_2^{(a,b)}$, and $\beta_3^{(a,b)}$. The values of these coefficients are determined using a least squares technique over an arbitrary span length of previously observed data. $z_n^{(a,b)}$ is a random variable representing channel noise on day n, channel a and band b.

$$x_{n+3}^{(a,b)} = \beta_1^{(a,b)} x_{n+2}^{(a,b)} + \beta_2^{(a,b)} x_{n+1}^{(a,b)} + \beta_3^{(a,b)} x_n^{(a,b)} + z_n^{(a,b)} \qquad (1)$$

Using the forecasting features of this model, one day and two day ahead predictions were calculated for Band 1 Channel 5. This channel was chosen arbitrarily and similar analyses were done on the remaining channels. Figure 2 shows the observation curve as well as the one day prediction and two day prediction curves.

**Figure 1: Radar waveform power output data (kW)**

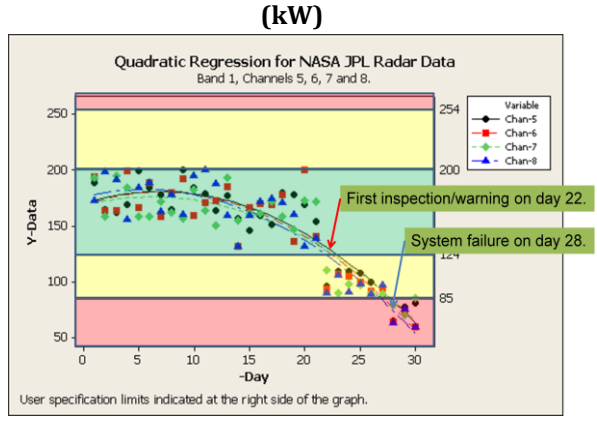
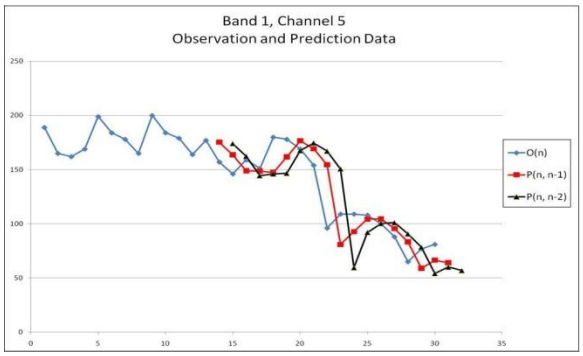
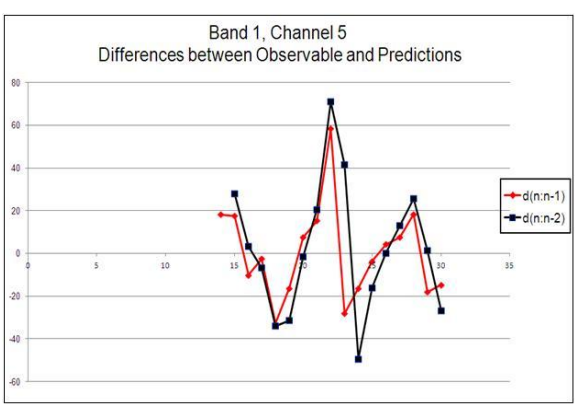


**Figure 2: Observation curve and NASA/JPL one day (red) and two day (black) prediction curves**



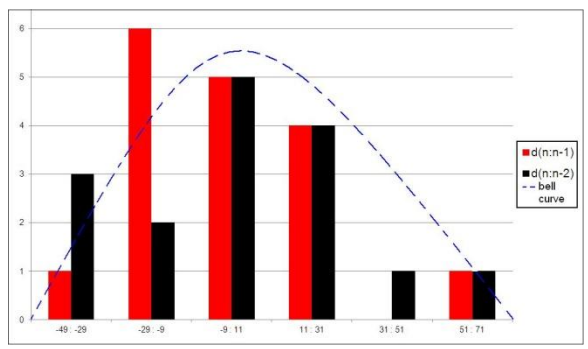

This model assumes that the channel noise is negligible with expected value zero: $E\left[z_n^{(a,b)}\right] = 0$. To validate and verify this assumption, the errors of the prediction curves were calculated and plotted. The errors are the differences between the observations and the predictions for a particular day. Figure 3 shows the error curves for the autoregressive forecasting model. We see that although most errors fluctuate around zero, there are a few errors that are very large and of concern. This type of plot is very useful because it allows us to see the accuracy of the predictions.

**Figure 3: NASA/JPL error curves for one day (red) and two day (black) predictions**




Another useful plot is the histogram of the errors for the prediction curves (Figure 4). This plot allows us to determine whether the underlying assumption of a negligible channel noise is reasonable. This histogram should look approximately like a bell curve. We see that this assumption is not grossly violated and eases our previous concern of large errors.

**Figure 4: NASA/JPL error histograms for one day (red) and two day (black) predictions**




After this model was fit to the data, our NSWC PHD team applied established six-sigma tools to the data. Using the one day predictions calculated from the NASA/JPL model, the ratio of prediction difference to observation with daily rational subgrouping was calculated. Using this rationalized data, an X-bar R chart was created. Figure 5 shows this X-bar R chart. In this chart, each point represents the channel group (5-8) for that day after rational subgrouping. Notice that the X-bar R chart shows that there are no out of control conditions before nor after the day of the actual failure, which was on day 22. This indicates relative data stability with this measure.

**Figure 5: X-bar R Chart of rationalized data**

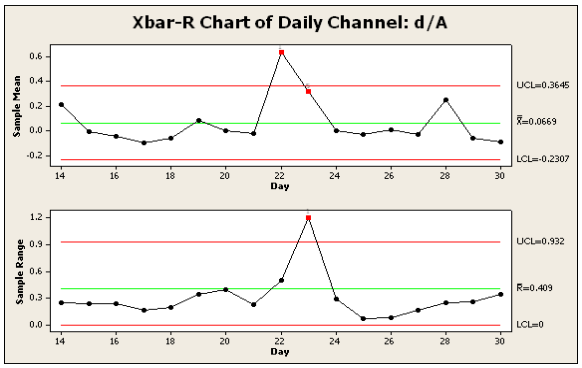
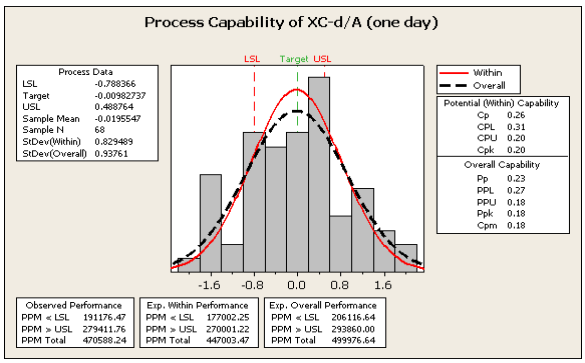


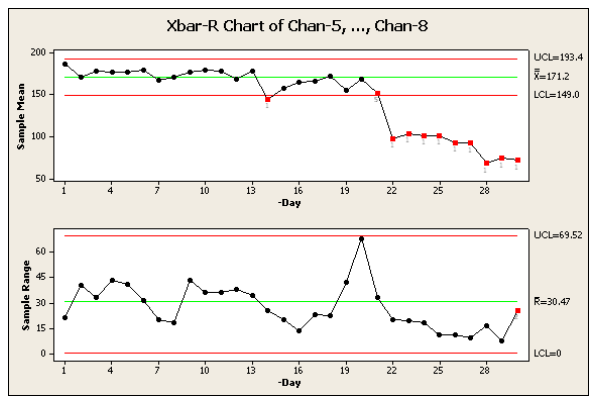

**Figure 6: Capability for one day predictor**




Even containing a failure scenario we still found about 50% of the one day predicted values were within ±10% of the corresponding observed value. This is reasonable given the high levels of noise in the data. Despite this heavy noise, using control charts and modified parameter protocols proved to be extremely useful. Figure 7 shows an X-bar R chart of our data using the first 19 observations (days) to establish the control chart parameters. This control chart also takes into account the channel grouping (5-8). As is evident from the X-bar chart, there seems to be a clear downward trend signaling a shift with two specific points of interest: day 14 and day 21. These two days have signaled that an out of control condition is occurring.

Interestingly enough, day 21 is one day prior to the actual failure (warning) which occurred on day 22. The R chart shows something similar occurring at day 20, which is two days prior to the actual failure. This signal is an indication of a significant disassociation of values within the channel group. Considering both of these charts, one can deduce that a failure will be happening in the near future after day 21.

**Figure 7: X-bar R chart of channels 5-8**




Using the predictions from the NASA/JPL model, we were able to predict "out of control" conditions which seemed to signal a imminent failure. Figure 8 shows an X-bar R chart of the predictions using the first 19 observations (days) to establish the control chart parameters. Using this combination, an X-bar control failure would occur on day 21 which coincides with day 21 observed data actually registering as an X-bar control chart "out of control" condition (Figure 7). Consequently, we have just shown that we have a valid and verified pre-failure "out of control" one day prediction. Furthermore, we have also shown that we may have a method to predict pre-failure

"out of control" conditions. A system of checks and balances is suggested to verify that the "out of control" predictions actually come in as "out of control" observations. After selecting the most suitable control chart and when both the prediction and observation for a particular day register as "out of control," then we declare failure is imminent. This occurrence would signal to the operator to take the system offline and proceed with preventative maintenance, take corrective actions, or find alternate resources to cover the mission requirements.

**Figure 8: X-bar R chart of the channel group (5-8) using NASA/JPL predictions**

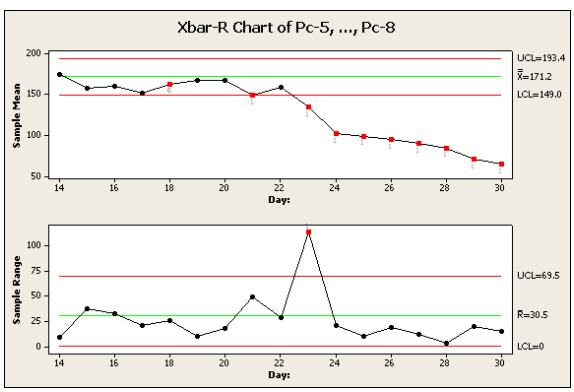
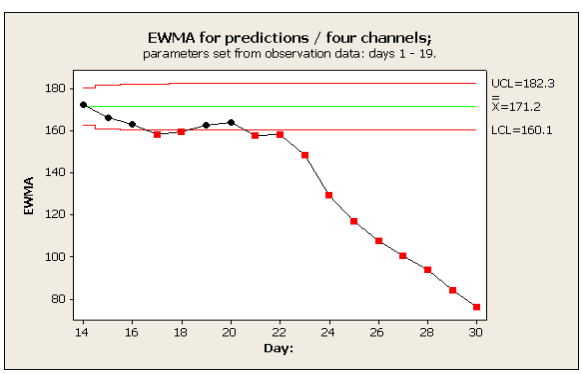



**Figure 9: EWMA used for predictions on the channel group (5-8)**




Using the NASA/JPL predictions, a second type of control chart was implemented. Exponentially Weighted Moving Average (EWMA) control chart parameters were derived from the first 19 channel group observations (days). Using these parameters, Figure 9 shows the plot of the predictions and a unique situation appears. The control chart in Figure 9 in conjunction with the NASA/JPL ePrognostics tool predicts an EWMA out of control condition on day 21. Referring back to our protocol, we need to verify that the observed data on day 21 reports as out of control. Figure 10 is an EWMA control chart for the observations. Notice that the data on day 21 does register as an EWMA control chart out of control condition. Again, we have a valid and verified pre-failure prediction for next day predictions.

**Figure 10: EWMA used for observations of the channel group (5-8)**

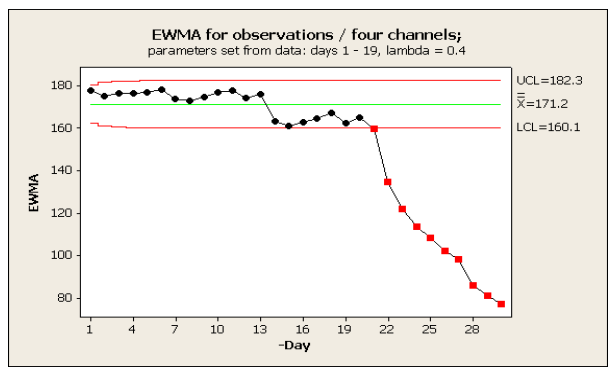


**Figure 11: NASA/JPL ePrognostics prediction for channel 8 with parameters from days 1-19**

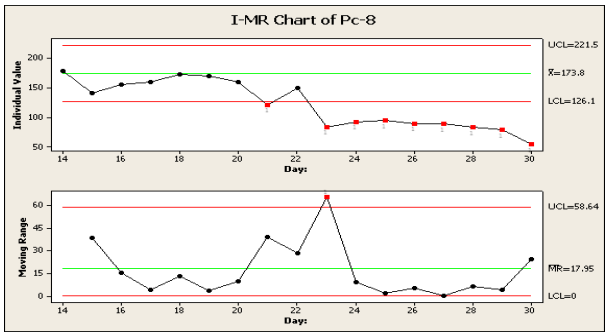
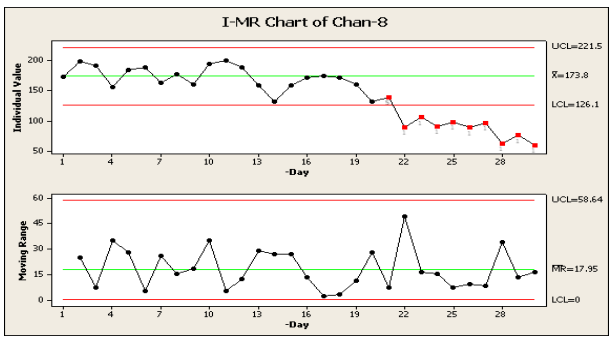



**Figure 12: Channel 8 observations with parameters from days 1-19**




The parameters for the I-MR (Individuals & Moving Range) charts in Figures 11 and 12 are based on the channel 8 observations for days 1 through 19. An interesting situation is noted. The I-MR chart of the channel 8 predictions (Figure 11) in conjunction with the NASA/JPL ePrognostics tool would predict an Individual out of control condition is going to occur on day 21 (one day prior to the actual warning). Note that in Figure 12, the I-MR chart of channel 8 observations, the data on day 21 does register as an Individual control chart "out of control" condition. Once more, we have a valid and verified pre-failure prediction for next day predictions. However, there is one more important difference in the prediction control charts. The X-bar R (Figure 8) and I-MR (Figure 11) predict a control recovery for day 22; which does not happen. Hence, a type-II error has occurred here. The EWMA chart (Figure 9) did not indicate a recovery on day 22.

In addition to the NASA/JPL prediction algorithm, we also considered other prediction methods. Furthermore, we developed a synthetic quantitative coefficient of determination to compare the prediction algorithms. One of the tested prediction algorithms was another autoregressive forecasting model. This model assumes that each observation is a linear function of the previous two observations. Equation 2 defines the autoregressive forecasting model where for any day "n", the observed value for that day on channel a and band b is written: $x_n^{(a,b)}$. Hence, as measured in observation cycles from day n, the observation two days in the future $x_{n+2}^{(a,b)}$ is considered to be equal to a linear combination of observations: one day forward, $x_{n+1}^{(a,b)}$; and on day n, $x_n^{(a,b)}$; with coefficients $\beta_1^{(a,b)}$ and $\beta_2^{(a,b)}$ again determined by a least squares method. $z_n^{(a,b)}$ is a random variable representing channel noise on day n, channel a and band b.

$$x_{n+2}^{(a,b)} = \beta_1^{(a,b)} x_{n+1}^{(a,b)} + \beta_2^{(a,b)} x_n^{(a,b)} + z_n^{(a,b)} \quad (2)$$

Another approach was considered, interpreting the problem in a slightly different way. This prediction algorithm relates the next channel random fluctuation as a function of the previous

channel random fluctuations. This is the K model and is defined by the following sequence of equations (equations 3-7) where for any day "n", the observed difference between day n and day n-1 is written: $\Delta_n$. Hence, as measured in observation cycles from day n, the difference two days in the future $\Delta_{n+2}$ is considered to be equal to a linear combination of differences: one day forward difference, $\Delta_{n+1}$; and the difference on day n, $\Delta_n$; with coefficients $\omega_1$, $\omega_2$, and $\omega_3$.

$$\Delta_n = x_n - x_{n-1} \tag{3}$$

$$\Delta_{n+2} = \omega_1 \Delta_{n+1} + \omega_2 \Delta_n + \omega_3 \Delta_{n+1} * \Delta_n \tag{4}$$

where

$$d = \begin{bmatrix} \Delta_n \\ \Delta_{n-1} \\ \Delta_{n-2} \\ \vdots \end{bmatrix} \quad \omega = \begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \end{bmatrix} \tag{5}$$

$$\Delta = \begin{bmatrix} \Delta_{n-1} & \Delta_{n-2} & \Delta_{n-1} * \Delta_{n-2} \\ \Delta_{n-2} & \Delta_{n-3} & \Delta_{n-2} * \Delta_{n-3} \\ \Delta_{n-3} & \Delta_{n-4} & \Delta_{n-3} * \Delta_{n-4} \end{bmatrix} \tag{6}$$

$$\omega = (\Delta^T \wedge \Delta)^{-1} \Delta^T \wedge d \tag{7}$$

$\wedge$ is an observation weighting/screening matrix.

Another approach, called Linear Differencing, was also considered. The following equations (equation 8-9) define this model where for any day "n", the observed value for that is written: $x_n$. Hence, as measured in observation cycles from day n, the observation two days in the future $x_{n+2}$ is considered to be equal to a linear combination of observations: one day forward, $x_{n+1}$; and on day n, $x_n$; with coefficients $\beta_1$ and $\beta_2$. The coefficients in this model as well as previous models were calculated using

$$x_{n+2} = \beta_1 x_{n+1} + \beta_2 x_n \tag{8}$$

$$x_n = c_1 * \alpha_1^n + c_2 * \alpha_2^n \tag{9}$$

Least Squares, Iterative Least Squares, Yule-Walker, and Hannan-Rissanen numerical techniques. After rigorous application and testing on all of the preceding models, the NASA/JPL autoregressive model performed the best. We arrived at this conclusion based on detailed error analysis as well as our synthetic quantitative coefficient of determination. Table 1 shows the coefficients of determination for the various prediction algorithms that were considered. The NASA/JPL autoregressive forecasting model outperformed the other models considering the widest spectrum of operational and simulated data.

**Table 1 : Next day prediction coefficients of determination**

| NASA/JPL AR(3) | NASA/JPL AR(2) | K Model | Linear Diff. |
|---|---|---|---|
| 0.665 | 0.700 | 0.554 | 0.662 |

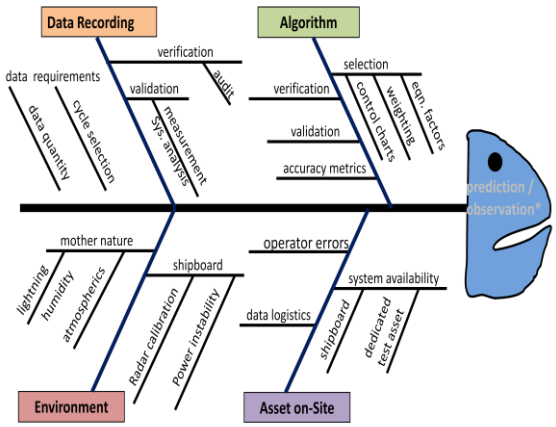
These results were not typical; they represent the best fit obtained from any of the operational data sets.

## CONCLUSION

We were able to show that the NASA/JPL ePrognostics tool had the best single predictor algorithm using actual data. Additionally, we used heavy modeling and

simulation (Monte Carlo methods) with synthetic quantitative measures to analyze and assess their performance. Control chart methodology and rational channel subgrouping with the NASA/JPL predictions appeared to be an effective and verifiable failure prediction technique on this data set. The day 21 "out of control" prediction precedes the day 28 actual system failure by 8 days. Day 22 was an operational inspection specification warning, which for our prediction purposes we took to be a "system failure." However, the operational data was in general very noisy (low signal to noise ratio) and the reasons for this need to be researched. Regarding the noise, the team brainstormed various potential causes and captured this discussion in a Cause and Effect (C&E) diagram.

**Figure 13: Cause and Effect Diagram for data noise**




* NASA/JPL expressed concerns regarding accuracy and instability of the provided data.

## FUTURE RESEARCH

The team recommends continuing the project into the next phase. With the inclusion of enhanced algorithms, formal observation screening and weighting, and control charts with parameter selection and prediction protocols, we believe there is sufficient objective evidence which substantiates our opinion that a valid and useful operational product: "predicting immanent failures in advance of them happening" might be developed. We need (in addition to further research time) actual, controlled operational data, obtained in a scientific manner with data collection notes and detailed failure information. Also, the noise evident in the data needs to be addressed and somehow mitigated; data sampling methods and applications, and other (or alternate) data capture points identified and explored.

## REFERENCES


Benbow, Donald W and Kubiak, T.M., *The Certified Six Sigma Handbook.* Milwaukee: ASQ Quality Press, 2005.

Blanc-Lapierre, A. and Fortet. R., *Theorie des Functiones Aleatoire.* Newark: Gordon and Breach Publishing Company, 1968.

Borror, Connie M. (ed), *The Certified Quality Engineer Handbook, 3rd Edition.* Milwaukee: ASQ Quality Press, 2009.

Brockwell, Peter J. and Davis, Richard A., *Introduction to Time Series and Forecasting, 2nd Edition.* New York: Springer-Verlag, 2002.

Devore, J. L., *Probability and Statistics for Engineering and the Sciences*, 2nd Edition. Pacific Grove: Brooks/Cole Publishing Company, 1987.

Papoulis, A., *Probability, Random Variables and Stochastic Processes.* New York: McGraw-Hill Book Company. 1965.

Parzen, E., Modern Probability Theory and its Applications. New York: Wiley&Sons. 1960.

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